

ADVANCES IN NEURAL OPERATORS FOR SCIENTIFIC MODELING

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MINISYMPOSIUM

Modeling complex systems typically involve the evaluation of integro-differential operators that map fields (e.g., initial and boundary data, parameter fields) into solution fields. These operators are traditionally approximated using discretization approaches such as finite difference or finite elements. An emerging alternative approach is to approximate the operators with neural operators, that is, with deep-learning based models. Once trained, neural operators are much faster than traditional computational models, and they are advantageous in different contexts, e.g., in inverse problems, uncertainty quantification and in high-dimensional problems. In addition, neural operators can naturally assimilate observations and experimental data and therefore can potentially achieve higher fidelity than traditional models.

Several neural operator architectures have been proposed in the literature, e. g., Deep Operator Networks, Fourier Neural operators, Kernel Graph Operators, featuring different strengths and weaknesses.

This mini-symposium focuses on both theoretical and computational aspects of neural operator modeling, covering the design of neural operators, their training and use in the context of computational mechanics applications.

Topics of interest include, but are not limited to: training methods using multi-modal or multi-fidelity data, training approaches that are parallel and scalable, strategies to enforce physical constraints or property preservation, design of hybrid models combining traditional simulation codes with neural operators, accuracy and epistemic uncertainty of neural operators.